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Exploring Independent Feature Extraction Techniques for Context-based Image Retrieval in Healthcare

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***Abstract*—In medical informatics, developing efficient image retrieval methods is vital for the research and development of diagnosis and treatment processes. This study evaluates three different feature extraction methods that could be beneficial for enhancing context-based image retrieval (CBIR) in medical imaging applications. The techniques used are: Discrete** 1
Wavelet Transform (DWT) with Singular Value Decomposition (SVD), a combination of Sobel operators with DWT and SVD, 2
3 **and Autoencoders. Such hybrid feature extraction techniques are applied to gain salient characteristics and detect trends in the given image data. The BRATS dataset, which consists of various multi-modal MRI scans, is used in the study to validate the efficacy of each technique. To assess the performance of each technique, the InceptionNet V3 model is trained individually on each of these sets of feature-extracted images. Results show that, in terms of robustness and accuracy in classifying medical images, the DWT with SVD method outperforms the others. This research implicates choosing feature extraction techniques appropriately to improve CBIR systems in healthcare.**

Keywords— Feature extraction, context-based image retrieval, medical imaging, deep learning

I. Introduction

The need for efficient image retrieval techniques in healthcare informatics is pertinent. Rapid and relevant information retrieval from large databases of medical images can pave new avenues in research, diagnosis, and treatment. To meet this requirement, this study discusses three different feature extraction approaches that can be applied individually to further improve context-based image retrieval (CBIR) in the field of healthcare. Conventional CBIR systems may not be able to completely capture the variety and subtleties that can be perceived in medical images as they mostly rely on individual feature extraction techniques. The proposed methodology, in contrast, relies on a multimodal approach and explores the effectiveness of each hybrid technique.

First, a powerful neural network called Autoencoders is examined. It is used in feature extraction to learn hierarchical representations of visual data. By encoding the images to a lower-dimension feature space and then decoding it back again, they help in extracting abstract and distinct features from the images. Thus, it can increase the robustness and adaptability of the retrieval system. The paper also investigates the use of Sobel operators combined with Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD). Sobel operators play a crucial role in providing pertinent structural information by effectively identifying the edge and contour features in images. This method is implemented to capture complex textures along with spatial changes that can enhance the representation of image content when used with DWT and SVD.

Finally, the combination of DWT with SVD is examined as a hybrid feature extraction technique. By directly applying DWT to the image data and then SVD, it is hoped to uncover important features and patterns included within the multi-resolution representations. This study aims at comparing the performances of each approach in terms of accuracy and robustness.

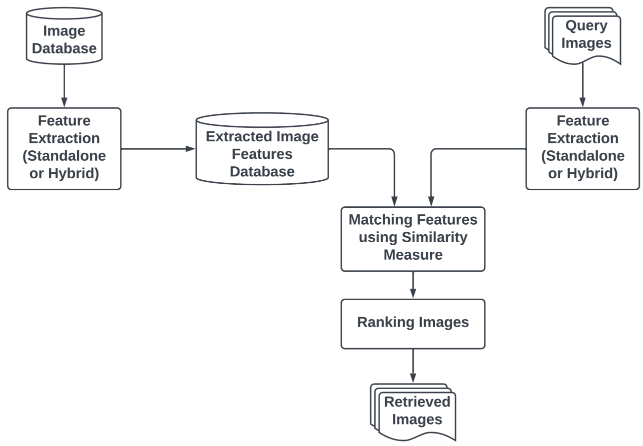

Fig. 1. Overview of Content-based Image Retrieval System Architecture

II. Literature Review

Initial efforts to improve the classification of medical diseases were focused on the challenges posed by vague, ambiguous, and incomplete data. In response to these challenges, a model known as Linguistic Neuro-Fuzzy with

Feature Extraction (LNF-FE) was introduced. This model incorporates feature extraction algorithms while producing membership values through the process of linguistic fuzzification. By minimizing the feature set and enhancing classification precision, this approach surpassed other methods on established benchmark datasets [1].

However, major progress has been made by employing CNNs in feature extraction for medical text analysis. This framework was designed to forecast disease risk and showed the capability of deep learning methodologies to generate both representative and adaptive features from medical datasets, thereby improving classification efficacy [2].

Another study presented was about multi-attribute fusion using neural network algorithms to enhance the robustness of feature descriptors. The proposed multi-feature fusion method was to enhance the feature extraction efficiency in medical images, including chest, lung, brain, and liver. In this experiment, the results showed high accuracy compared with the conventional approaches [3].

Significant progress is carried out by applying local binary pattern feature extraction methods coupled with convolutional neural networks for managing variations in tumour images. This operation enhanced the preciseness and reliability of texture feature representations, enhancing performance in diagnoses [4]. Similarly, another study applied CNNs to carry out feature extraction as well as classification of tumour images and insisted on the application of multi-channel input with such advanced convolutional architecture as DenseNet and Xception to enhance the accuracy of diagnostics [5].

The emerging methods include a feature extraction approach based on data distribution skew to improve the classification ability of the medical image dataset without the need for data augmentation. The method was found effective on multiple datasets, including diabetic retinopathy and brain tumours, and COVID-19-related chest X-rays with significant improvements over the traditional method [6].

At the same time, research in feature extraction modules and transfer learning was brought into algorithms, such as TrFEMNet, which optimized the classification of medical images by exploiting knowledge regarding the large image dataset. Transfer learning is rather beneficial for the assessment of medical images because the method was demonstrated by applying it to different datasets, including COVID-19, brain MRI binary classification, and brain MRI multiclass data [7].

A dynamic regional attention network named DRA-Net was proposed and utilized to further extend medical image segmentation. The model combined the advantages of CNNs and Transformers, especially for collecting local edge details as well as regionally inside medical pictures, feature extraction, and segmentation accuracy may be improved [8].

In addition to that, feature extraction from gene expression microarray medical datasets-based research introduced an innovative Multi-Class based Feature Extraction (MC-FE) technique. The technique first made use of PCA for preliminary feature extraction and employed the modified particle swarm optimization for feature selection, which improved classification performance in terms of cancer diagnosis [9].

Recent advances include fully automated systems relying on the detection of Alzheimer's disease based on brain MRI scans. Various feature extraction techniques were employed in the systems developed; however, ST ended up being the best. A comparative analysis of the different methodologies showed that the technique combining ST with the KNN strategy outperformed other methods in the detection of Alzheimer's disease [10].

In the final stage, a detailed analysis applied feature extraction techniques coupled with supervised machine learning algorithms to classify burns from radiographic medical images. The research demonstrated that a classification model based on SVM methodology could be developed resulting in higher classification accuracy of burns than previous approaches. [11]

Advancements in deep learning for medical image analysis, especially concerning brain MRIs, have been introducing both opportunities and challenges [12]. Even though deep learning models can manage the implicit management of feature extraction, understanding feature selection methodologies often helps further. Techniques about feature selection can interpret such complex models and make them more applicable to a wide range of diverse datasets.

III. Feature Extraction

Feature extraction is a critical preliminary stage within the machine learning framework, that deals with transforming raw data into a more interpretable and useful representation. It involves choosing relevant features that most efficiently describe the latent properties of the data distribution, followed by extracting a reduced number of these features. In general, training machine learning algorithms in low-dimensional feature spaces leads to improved performance results. Moreover, feature extraction filters out noise and irrelevant data from the model, thus improving the generalizability of the latter and reducing the chances of overfitting. The model enhances its ability to identify crucial relationships in the data by focusing on the most distinguishing characteristics, which leads to more accurate predictions and classifications.

A. Autoencoders

Due to their structural design, autoencoders can derive important features and patterns from the input data, making them a useful architecture in various applications of machine learning and image processing [13]. A study underscored the benefits of using denoising autoencoders to extract resilient features in noisy datasets and shed light upon their applicability in related machine learning problems [14].

B. Sobel Operators

Sobel operators are particularly good in bringing attention to locations within an image where the intensity changes quickly, they help in highlighting important edges and curves present in an image. Sobel operators are widely utilized in many image processing applications: edge detection, feature extraction, and image segmentation, among others, because of their ease of use and efficiency [15].

C. Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform is a powerful signal-processing technique that simplifies the decomposition of signals into their distinct frequency components in various resolutions.

DWT makes multi-resolution analysis easier in image processing and facilitates the extraction of fine and coarse features from images. Due to its flexibility, DWT is very useful for applications such as feature extraction, denoising, and image compression [16]. High accuracy in brain tumour detection from MRI images has been demonstrated by wavelet-based deep learning models. A deep wavelet autoencoder model demonstrated an accuracy of 99.3% along with a low validation loss of 0.1, thereby providing a rapid and dependable approach for tumour classification within clinical environments [17].

D. Singular Value Decomposition (SVD)

SVD decomposes a matrix into its singular vectors and singular values of the matrix, thus, representing the fundamental structure of the data through efficient representation and analysis [18].

Recent advancements in SVD-based techniques have focused on addressing specific issues in healthcare image retrieval, such as obtaining discriminative features from large-scale medical image datasets and combining SVD with deep learning architectures for better image representation. This approach has shown better predictive accuracy even in cases of incomplete datasets; hence overcoming a major challenge in medical data classification [19].

IV. Methodology

Using the University of Pennsylvania's BRATS dataset, the suggested methodology assesses three different feature extraction methods for context-based image retrieval in the medical field. To extract pertinent characteristics from the medical images, three different techniques — Autoencoders, Sobel Operators with Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD), and DWT with SVD — are applied individually. High-level, abstract features are learned and encoded in an unsupervised way using autoencoders. Significant information is captured by the encoder compressing the input data into a lower-dimensional latent representation. This information is then decoded to rebuild the input and reveal intricate patterns and anomalies in the images. DWT with SVD reduces dimensionality and extracts dominating structural and textural features by first utilizing DWT to break down the images into wavelet coefficients. In order to improve structural features, Sobel Operators with DWT and SVD uses the Sobel operator to detect edges. This highlights areas with notable variations in intensity that match to image borders. After that, DWT-SVD is applied to these edge-enhanced features for multi-resolution analysis, which captures both fine and coarse details. Following feature extraction, a machine learning method is used to classify each set of features. To find the best way for improving the precision and efficacy of CBIR in the medical field, the performance of each feature extraction strategy is assessed according to how well it can retrieve and classify medical images. The novelty lies in the integration of classical methods like Sobel operators with modern approaches such as DWT and SVD to enhance the ability of extracting both spatial and textural features. Unlike conventional CBIR methods, this hybrid framework systematically evaluates the robustness and efficacy of these techniques on the BRATS dataset, identifying the optimal approach to improve diagnostic precision in medical imaging applications.

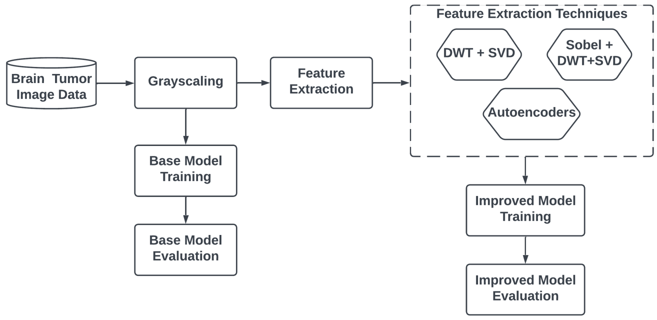

Fig. 2. Block Diagram of the proposed methodology

A. Data Collection and Preprocessing

The BRATS dataset includes various kinds of multi-modal MRI scans, that is, T1-weighted and T2-weighted images along with FLAIR images with the corresponding segmentation masks indicating the tumour locations. Each image is pre-processed through the extraction of features and the classification before all these processes. Standardization methods, which include scaling, normalization, and intensity normalization, form one of the most important stages of preprocessing. Application of these procedures ensures that the dataset will be coherent and homogenous and reduces biases found in these types of analyses while increasing precision in subsequent tests.

B. Feature Extraction

Feature extraction is an important step in the proposed methodology. It involves extracting relevant information from multi-modal MRI scans of brain tumours. We carry out three different techniques with respect to obtaining different sets of features relating to various aspects of the tumour's morphology, texture, and structure. Unsupervised learning is used by autoencoders to learn compact representations of image features, Sobel operators are used to emphasize edge features, and DWT is used for multi-resolution analysis. By incorporating dominating structural patterns and textural descriptors, SVD enhances the feature set even further. Through distinct methodology evaluation, we hope to determine the best method for context-based image retrieval in the field of healthcare.

C. Autoencoders

We extract latent features from the pre-processed MRI images using autoencoders that are highly regarded for their capacity to learn compact representations of input data. We train a denoising autoencoder on the dataset while we let the network encode key information about brain tumour morphology and tissue composition into lower-dimensional latent space representations. It reconstructs the original pictures whilst doing feature extraction from the encoder network, making it easy to extract suitable features that portray different tumour subtypes and the symptoms of the disease

D. DWT with SVD

The integration of DWT with SVD enhances our feature extraction technique, and it enables us to retrieve structural information along with textural information from MRI scans. DWT decomposes the images into wavelet coefficients incorporating the frequency contents by employing a varying resolution of analysis. Then, using the notion of SVD over these coefficients, texture descriptors together with the major structural patterns can be obtained. This two-stage approach yields a very large set of attributes combining both spatial and textural information, which offers substantial insight into the varied nature of brain tumours and is well-suited for detailed investigation.

E. Sobel Operators with DWT and SVD

This is another unique method of feature extraction that focuses on edge detection and multi-resolution analysis. Sobel operators are used to analyse the pre-processed MRI scans for gradient determination and to highlight the edges, which may describe a boundary of the tumour or structural anomalies. The DWT decomposes the images into various scales of frequency components, thus enriching edge characteristics with multi-resolution information. The retrieval characteristics are thus improved to discrimination capability, giving a more elaborate description of the form and geographic spread of the tumour.

F. Classification

In our approach, the feature classification phase evaluates the efficiency of the features extracted during the preceding phase. This study employed the InceptionNet V3 architecture, an advanced convolutional neural network, to achieve higher reliability for image classification tasks. The highly extensive and varied characteristics obtained with our three methodologies are suited for InceptionNet V3 because of its deep and complex architecture. Each set of derived features is presented to the InceptionNet V3 model, that was originally pre-trained on large-scale image datasets, and fine-tuned to optimum performance on our dataset. In the first stage of the classification procedure, individual set of features extracted from each technique is given to the InceptionNet V3 model. It parses those features using convolutional layers to extract subtle patterns and correlations in the data, an in-depth understanding of the content in medical images that enables the correct selection and retrieval of relevant images capability for deep learning methodology. Using the BRATS dataset as the training set, it is possible to train this model for the detection of exclusive patterns seen in various diseases. Later, the performance of the model is tested against the testing set with various metrics, including accuracy, precision, recall, and F1-score, to estimate the functionality of the model.

V. Results and Discussion

We summarize our findings using the following performance metrics: accuracy, recall, precision, and F1-score. These metrics give a comprehensive evaluation of the effectiveness of each approach in medical image classification on the BRATS dataset. Figure 3 illustrates the accuracy, precision, recall, and F1-score achieved by the methodologies discussed in this paper.

There were notable differences in the accuracy of the various approaches. With an accuracy of 76%, the DWT with SVD approach proved to be the most successful in differentiating between various forms of brain tumours. The Autoencoders technique, which achieved a 74% accuracy rate, followed closely behind. An accuracy of 69% was attained by the Sobel with DWT and SVD approach, suggesting its potential utility despite being marginally less successful than the top-performing methods. At 52% accuracy, the baseline method performed less than the enhanced feature extraction methods.

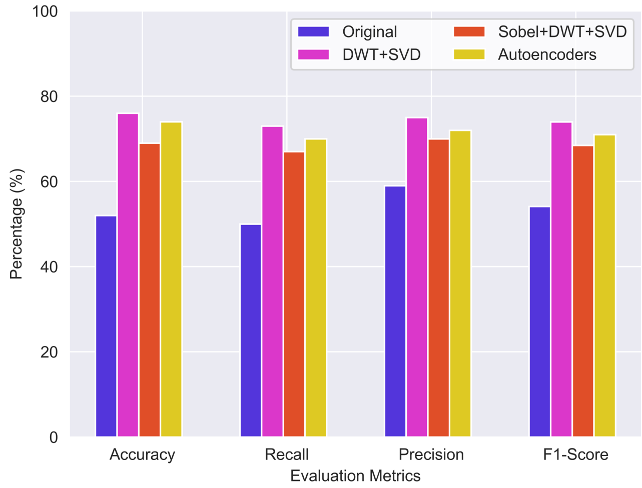

Fig. 3. Performance comparison based on evaluation metrics

A similar pattern was noted in the recall, which is a measure of the model's ability to accurately identify all positive instances. While considering other methods, the best-reported recall value was 73% for the DWT combined with the SVD method, thus showing a fewer number of instances. In addition to the result, the Autoencoders showed very good results with a recall of 70%. The Sobel with DWT and SVD method closely follows with a recall of 67%, whereas the baseline method lags with the lowest recall at 50%.

Compared to precision, which defines the proportion of true positive occurrences out of the available instances, DWT and SVD technique outperformed the competition with the highest precision value of 75%. The Autoencoders method ranked it closely at 72% precision while an excellent ability to reduce erroneous positives was depicted. The Sobel with DWT and SVD method yielded an accuracy of 70% with the baseline giving a much lower degree of accuracy and 59%, suggesting that the false positive rate is high.

More specific information on the effectiveness of each strategy can be accessed via the F1-score, where recall is balanced against precision. DWT with SVD came out again as the most effective with the highest F1-score of 73.98% with a better balance between recall and precision. Autoencoders followed with an F1-score of 70.67%, indicating a solid and consistent performance across both metrics. The Sobel with DWT and SVD technique achieved an F1-score of 68.46%, while the baseline method trailed behind with a significantly lower F1-score of 54.12%, underscoring its relative inefficiency.

Figure 4 depicts the training and validation loss curves, highlighting the performance of the various feature extraction techniques. The evaluation of training and validation loss provides a clear indication of each feature extraction technique's effectiveness and generalizability in classifying medical images from the BRATS dataset. Without applying any feature extraction techniques, the model, at the end of the training process, exhibited a training loss of 0.0154 and a significantly higher validation loss of 0.9706, indicating severe overfitting — where the model learns the training data exceptionally well but struggles with unseen data.

In contrast, the DWT with SVD technique achieved a more balanced performance, with a training loss of 0.1109

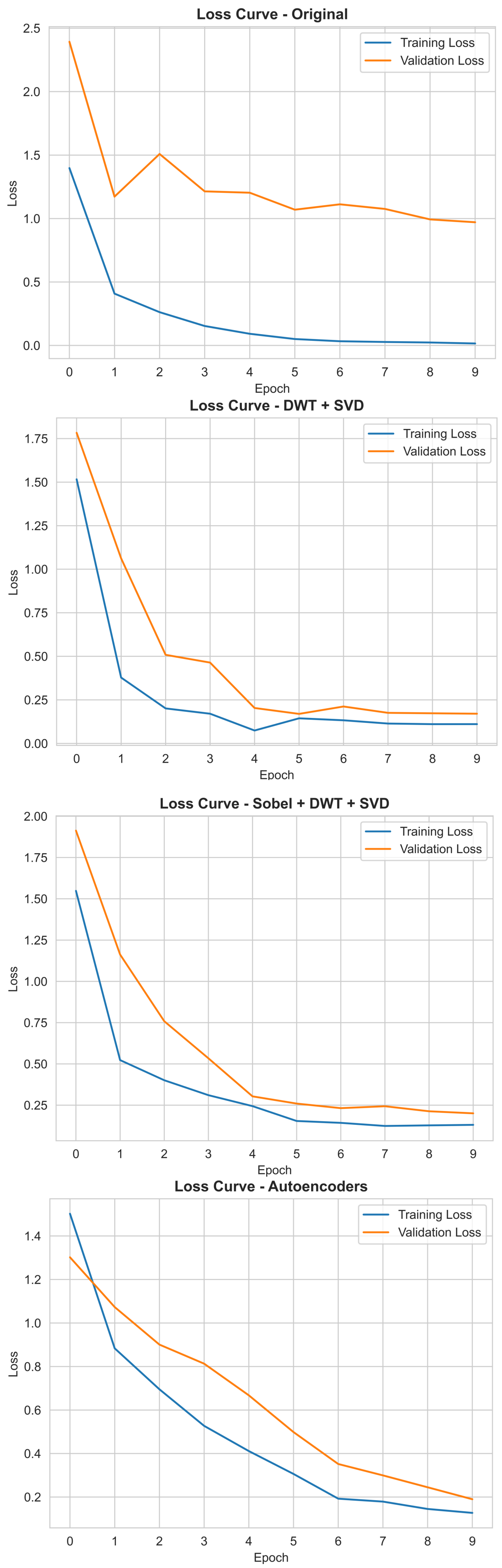

Fig. 4. Training and Validation Loss curves

and a validation loss of 0.1706, demonstrating effective generalization to new data. This suggests that DWT + SVD efficiently captures the essential features for classification while avoiding overfitting.

The Sobel with DWT and SVD method yielded a training loss of 0.1309 and a validation loss of 0.2006, indicating a reasonable performance but higher loss values compared to DWT + SVD, suggesting it may be less effective at extracting the most relevant features.

The autoencoder-based model showed a training loss of 0.1271 and a validation loss of 0.1899, reinforcing the ability of deep learning methods to capture and represent underlying image features, resulting in consistent performance across both training and validation datasets.

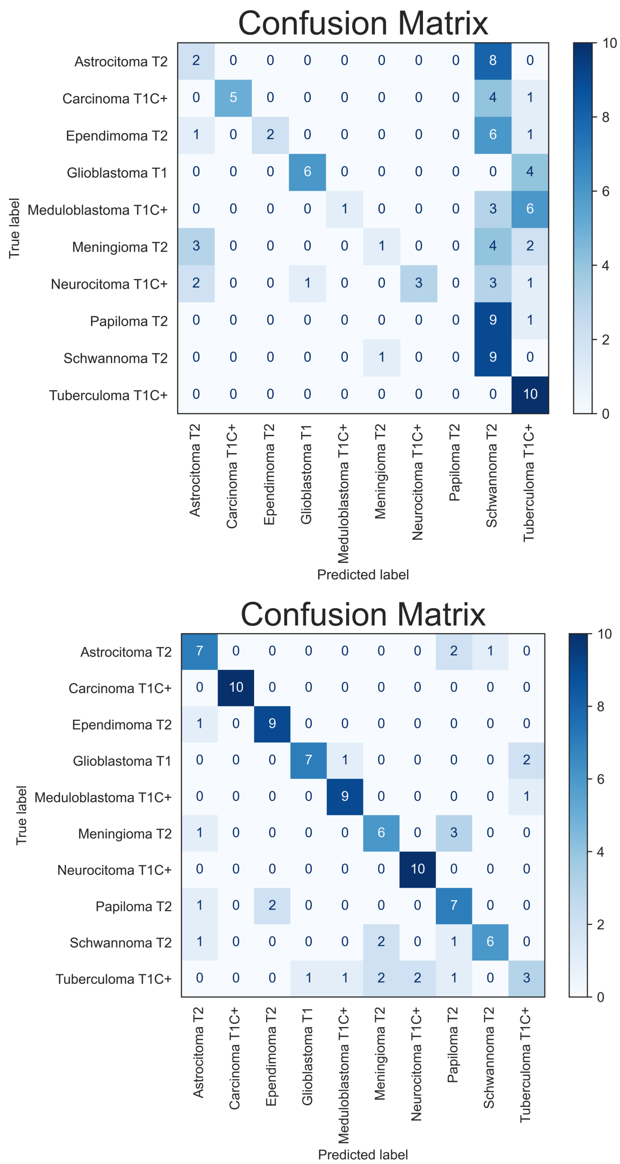

Fig. 5. Confusion Matrix: Baseline vs. DWT + SVD

Figure 5 depicts the confusion matrices corresponding to the test set, illustrating the performance of the baseline method and DWT with SVD technique. Clearly, when compared to the baseline method, the DWT with SVD strategy shows better overall accuracy, as seen by the higher number of correctly classified examples, particularly in categories Meduloblastoma T1C+, Neurocitoma T1C+ and Papiloma T2. In fact, the hybrid technique reduced misclassifications in Papiloma T2 by 70%, while achieving 100% correct classifications in Neurocitoma T1C+.

The advanced hybrid feature extraction techniques have significantly improved the classification of medical images. It is demonstrated that the best combination was attained between DWT and SVD which captured key image elements. Its ability to capture both global patterns and fine-grained details makes it particularly suitable for identifying subtle abnormalities in MRI scans. A strong performance by Autoencoders also showed how deep learning can be effective with complex image data. However, their performance was slightly limited by their reliance on the network's capacity to reconstruct relevant features accurately, which might have led to some loss of spatial details. The Sobel with DWT and SVD methods achieved respectable but ranked lower in comparison, which means it needs further refinement for better performance in the classification of medical images. Poor perfections in the baseline method and effective feature extraction for medical image retrieval make a difference in performance.

VI. Conclusion

The three feature extraction methods discussed in the paper are Autoencoders, a combination of DWT and SVD, and Sobel operators combined with DWT and SVD in order to support context-sensitive retrieval of medical images in the specific domain of the BRATS dataset, containing multi-modal MRI scans. The DWT with the SVD technique outperformed the rest in terms of structural and textural aspects with an accuracy of 76%, precision of 75%, recall of 73%, and F1-score of 73.98%. Autoencoders also performed well, as they could learn even more concise feature representations, and hence achieved an F1-score of 70.67%. Sobel operators combined with DWT and SVD produced meaningful edge enhancement and discrimination capability; although they were slightly less effective, producing an F1-score of 68.46%. In conclusion, the results show that appropriately applying feature extraction techniques to CBIR systems can make them perform better for healthcare applications. Future research attempts could further enhance such methodology and investigate their generalizability across various medical image datasets, thereby generalizing the results and enhancing the precision and efficiency of diagnosis in a clinical setting.

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